On soil health and the pivotal role of ~~proximal~~sensing

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Abstract. Soil underpins the functioning of all terrestrial ecosystems, yet its accelerating degradation demands urgent action. Sustainable soil management is ~~crucial to~~essential for preventing further soil degradation ~~of the non-renewable soil~~ and achieving ~~sustainability~~sustainable land use. ~~While the soil health concept has gained popularity as a means to this end and has been integrated into the policies of m~~Many countries and supranational organisations have embraced the concept of soil health and integrated it into their policies. However, critical gaps persist in the operational assessment of frameworks that evaluate soil health. We need ~~an accurate~~to establish a clear, objective definition and a scientifically robust assessment framework ~~for~~to effectively ~~measuring, and managing soil health, a framework that can be communicated effectively to the policy makers and to stakeholders~~measure and manage soil health, ensuring transparent communication with policymakers and stakeholders. A more coherent approach to soil health is urgently needed because a lack of operational procedures to measure soil health results in policies that overlook the soil and prioritise management measures. ~~Linking soil health, the provision of ecosystem services in line with selected UN Sustainable Development Goals (SDGs) provides an effective link with the policy arena focusing on sustainable development.~~ ~~W~~Here, we review the literature on soil health, its conceptualisation, the current criteria for selecting indicators and thresholds, ~~as well as~~and the implementation of current soil health assessment frameworks. Most published studies on soil health focus on agriculture; ~~however,~~yet current environmental challenges demand a broader perspective that includes ~~various terrestrial~~other ecosystems~~is needed~~. ~~Soil health assessments should not be limited to agricultural contexts. We highlight the significant potential of advanced sensing technologies to improve current soil health evaluations, which often rely on traditional methods that are time-consuming and costly.~~ We propose ~~a soil health assessment~~an integrative framework ~~that prioritises ecological considerations and is free from anthropogenic bias. The proposed approach leverages modern technological advancements, including proximal sensing, remote sensing, machine learning, and sensor data fusion.~~with a balanced socio-ecological perspective that uniquely leverages modern technologies, like soil and remote sensing, statistical modelling, machine learning and artificial intelligence. This combined use of technologies enables objective, quantitative, reliable, rapid, cost-effective, and scalable ~~, and integrative soil health~~ assessments of soil health, helping to meet the urgent demand for effective and sustainable soil management. By centring ecological integrity within our integrated sensing-technology-based framework and balancing this with ecosystem services considerations, we ensure that soil health assessments serve both environmental stewardship and the UN Sustainable Development Goals (SDGs), providing a robust scientific foundation for soil-related policy.

1 Introduction

Soil is essential for ecosystem functioning and human society. Healthy soil improves water quality by enhancing infiltration, reducing erosion, and mitigating pollution (Zimnicki et al., 2020; Keesstra et al., 2021). It contributes to climate change mitigation by sequestering carbon, buffering soil biota from rapid environmental changes, and regulating greenhouse gas emissions (CO_2, CH_4, N_2O) (Lal, 2016).

~~Soil also supports human health by providing nutrients through food, suppressing pathogens, offering medicinal resources, and aiding immune system development through exposure to environmental microbiomes~~Soil also serves as a foundation for human communities and societal functioning, by providing nutrients through food production, offering medicinal resources, and supporting immune system development through exposure to beneficial environmental microbiomes (Pepper, 2013; Brevik et al., 2020). ~~However, degraded or contaminated soil can harm human health through nutrient deficiencies or exposure to toxins and pathogens~~Conversely, when soils are degraded or contaminated, they can threaten human health through reduced food quality, nutrient deficiencies, or exposure to toxins and pathogens (Brevik et al., 2020; Oliver and Brevik, 2024).

The ~~global importance of soil has been recognised by the United Nations' Sustainable Development Goals (SDGs), adopted in 2015~~United Nations' Sustainable Development Goals (SDGs), adopted in 2015, recognised the global importance of soil. Amongst others, the SDGs address food insecurity (SDG1/2), water scarcity (SDG6), climate change (SDG13), biodiversity (SDG15), and health (SDG3) (Bouma, 2014; Keesstra et al., 2016). SDG 15.3 explicitly aims to halt and reverse soil degradation by 2030. The concept of soil health is central to assessing soil degradation, as its indicators reflect the severity of degradation. Global frameworks, such as the United Nations Convention to Combat Desertification (UNCCD) and United Nations Framework Convention on Climate Change (UNFCCC), also emphasise sustainable soil management and the role of soil in carbon sequestration (Lehmann et al., 2020).

~~Despite this recognition, soil degradation remains widespread (FAO and ITPS, 2015).~~Despite this recognition, soil health continues to decline globally through widespread degradation (FAO and ITPS, 2015) that diminishes ecosystem capacity to provide essential goods and services (Food and Agriculture Organization of the United Nations, 2025; Kraamwinkel et al., 2021). Soil is a non-renewable resource formed over millennia; its degradation threatens biodiversity, climate stability, human well-being, and planetary sustainability (Alexander, 1988; Doran, 1996; Lehmann et al., 2020). Agricultural expansion and deforestation exacerbate soil degradation (Dickson et al., 2021; Burrell et al., 2020), with approximately 80% of global arable land affected by desertification, erosion, salinisation, or carbon loss (Prăvălie et al., 2021). ~~Growing~~Intensifying climate change and growing global demand for food, water, energy, and raw materials further ~~strains soil resources~~compound these pressures (Keesstra et al., 2016). Sustainable development, as defined in the Brundtland Report, involves meeting current needs without compromising those of future generations (WCED, 1987). Sustainable soil management is urgently needed.

Many nations have enacted policies to protect their soil. The EU's Soil Strategy for 2030 highlights soil contributions to ecosystem services and includes initiatives like 'Living Labs and Lighthouses' to develop region-specific soil health practices (European Commission, 2021; Bouma, 2022b). In the U.S., programs such as the Conservation Stewardship Program and the 2018 Farm Bill incentivise practices like crop rotation, cover cropping, and rotational grazing. ~~However, most policies focus on car-~~

~~bon sequestration and water quality in agricultural contexts rather than the broader, multifaceted dimensions of soil health.~~ Australia's National Soil Strategy outlines a 20-year plan to improve soil health ~~at a national level~~nationally, extending beyond state-specific initiatives (DAWE, 2021). Most current policies focus primarily on specific soil functions, particularly carbon sequestration and improving water quality in agricultural systems. However, they often overlook the broader ecological functions of soil, such as supporting biodiversity, facilitating nutrient cycling, regulating pests, and providing habitats across various ecosystems.

Despite these efforts, significant challenges remain, particularly in defining, measuring, and implementing soil health assessments. Policies often prioritise management practices without addressing broader ecosystem services (Baveye, 2021; Bouma, 2021; Bouma and Scrope, 2024). The debate on soil health frequently emphasises agricultural perspectives, neglecting the ~~ecological needs of ecosystems themselves~~intrinsic ecological functions that enable the self-regulation and resilience of ecosystems independent of human-centric goals. Societal and cultural values, while vital, complicate definitions and hinder objective, quantitative measurements (Lehmann et al., 2020; Janzen et al., 2021; Friedrichsen et al., 2021). ~~A pragmatic focus on environmental ecosystem services can simplify assessments while maintaining relevance.~~ Ecosystems ~~themselves~~ have intrinsic needs that must guide research, as highlighted in SDG 15, 'Life on Land'. ~~Broader societal values, including cultural and aesthetic dimensions, as well as human well-being (e.g., self-determination and connectedness), are relevant but complicate definitions and measurement (Lehmann et al., 2020; Janzen et al., 2021; Friedrichsen et al., 2021). A pragmatic focus on environmental ecosystem services simplifies assessments and enables quantitative evaluations within socioeconomic contexts while maintaining relevance~~A pragmatic focus that restricts soil health assessments to environmental ecosystem functions allows objective, quantitative evaluations of soil health, while still recognising its broader socioeconomic relevance (Baveye, 2021).

~~For soil health to serve as a practical scientific framework, it must be clearly defined and objectively measured. Effective indicators should provide insights into underlying mechanisms and support informed soil management decisions~~To be a practical scientific approach in soil and land management, soil health must be clearly defined and measured objectively. Reliable indicators should reflect the underlying ecological mechanisms and guide effective soil management decisions. As soil degradation accelerates in many regions, there is an urgent need for assessment methods that are scientifically robust and operationally efficient. Current methods are often outdated, costly, and limited in scope, frequently lacking quantitative links between measured indicators and real-world outcomes (Wood and Blankinship, 2022). ~~Advances~~To address the scale and urgency of contemporary soil challenges, advances in information technology, sensors, machine learning and artificial intelligence (AI) offer promising avenues for rapid, precise, and cost-effective soil health assessments at the appropriate spatial and temporal scales (Viscarra Rossel et al., 2011; Shen et al., 2022; Baumann et al., 2022; Reijneveld et al., 2024). These innovations ~~have the potential revolutionise~~can potentially transform soil health monitoring and deepen our understanding of soil functions and ecosystem sustainability (Viscarra Rossel and Bouma, 2016).

Thus, our objectives are to:

1. ~~Analyse current views on soil health and methods for assessing it~~Evaluate contemporary perspectives on soil health and explore current assessment methods, while pinpointing significant limitations and gaps within these approaches.

2. ~~Propose procedures for developing an objective, scientifically sound, and effective framework for soil health assessment~~Propose a new framework for assessing soil health that integrates ecological principles with socio-cultural considerations, leveraging soil sensing and balancing environmental sustainability and community needs..

3. Describe ~~the potential of~~how soil sensing and other ~~innovative~~ technologies ~~to measure indicators and~~can support the proposed framework, enhance ~~assessments of~~ soil health assessments and their practical implementation.

2 Defining soil health

The evolution from ‘soil fertility’ to ‘soil quality’ and, ultimately, to ‘soil health’ (Bünemann et al., 2018; Lehmann et al., 2020) reflects growing scientific awareness of soil’s broader functions beyond crop production. Early assessments focused on soil fertility, defined as the soil’s capacity to support crop production (Patzel et al., 2000; Bünemann et al., 2018). Over time, this expanded to include soil’s roles in water and air quality and contributions to plant and animal health, leading to the concept of soil quality (Mausel, 1971; Bünemann et al., 2018). Wallace first used the term ‘soil health’ in 1910, initially referring to soil fertility (Wallace, 1910; Brevik, 2018). By the 1990s, as understanding of soil biology and its environmental and human health roles grew, the contemporary concept of soil health emerged, encompassing soil’s multifunctionality in ecosystem functions and services (Brevik, 2018; Lehmann et al., 2020; Janzen et al., 2021; Friedrichsen et al., 2021).

The terms ‘soil health’ and ‘soil quality’ are often used interchangeably but differ conceptually. Soil health refers to the current condition of a specific soil, akin to a patient’s health status, while soil quality describes the expected range of health values for a given soil type, comparable to health standards for demographic groups (Bonfante et al., 2020). The analogy with human health makes "soil health" a compelling term for engaging stakeholders. Soil fertility, though narrower in scope, remains relevant in agronomic contexts as one function of soil health (Kuzyakov et al., 2020).

Figure 1 illustrates the progression and broadening scope of the soil health concept over time. Early definitions of soil health, such as “the continued capacity of a living soil to function within ecosystem boundaries to sustain biological productivity, maintain environmental quality, and promote plant, animal, and human health” (Doran and Parkin, 1994; Doran, 1996; Doran et al., 1997), remain widely applicable. Modern refinements link soil health to ecosystem services and international policy frameworks, such as the United Nations’ SDGs, where soil’s contributions to ecosystem services align with global sustainability goals (European Commission, 2021).

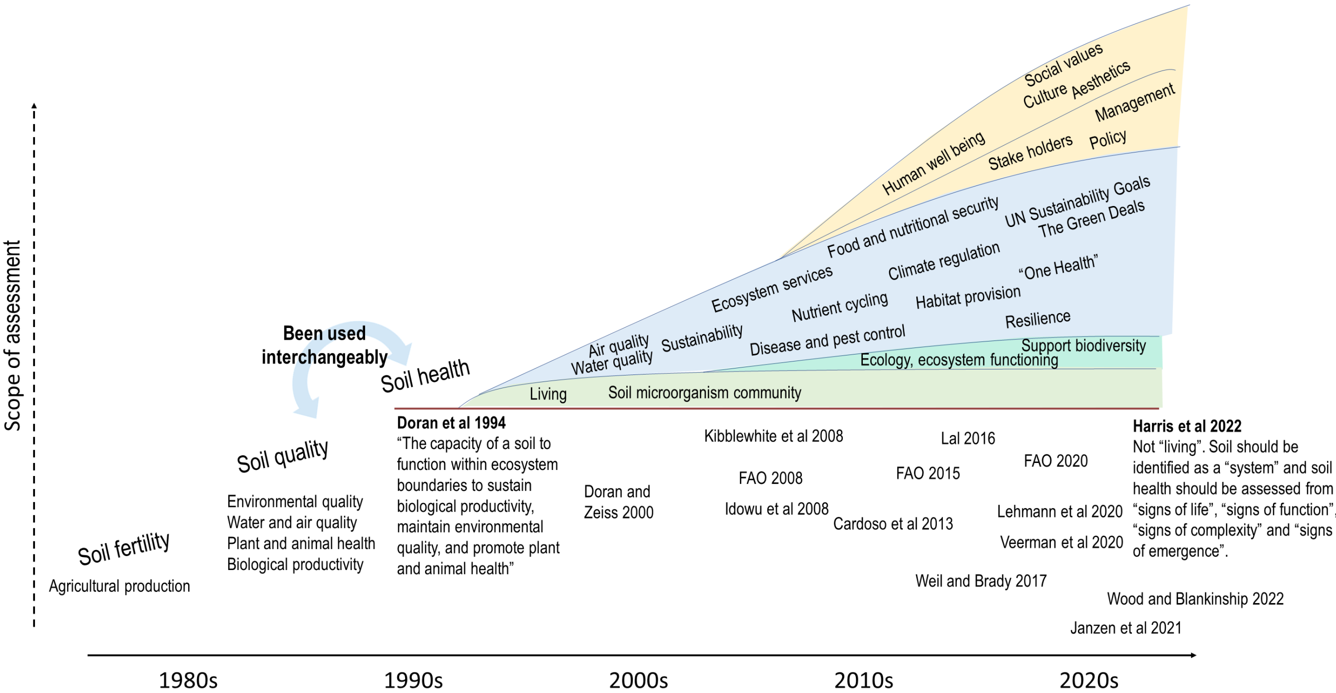

Figure 1. The evolution of soil assessment from soil fertility to soil quality to soil health, reflecting an expanding scope. Keywords and elements from key papers on soil health are arranged chronologically.

More recent soil health definitions emphasise soil organisms. This focus addresses the historical neglect of soil biology compared to chemical and physical properties (Pankhurst et al., 1997). It underscores that only living organisms exhibit health (Harris et al., 2022), a statement challenged by Bouma (2022a), who emphasises that physical and chemical conditions are also crucial for soil organisms and that an integrated approach, certainly including biological indicators, is needed. Some authors therefore describe soil health as 'the biological integrity of the soil community, that is, the balance among organisms within the soil and between soil organisms and their physical and chemical environment' (Weil, 2017). Soil biology is a critical indicator of soil health, and there are some new methods available for its characterisation (Reijneveld et al., 2024).

Many authors adopt a broader, holistic view of soil health, highlighting its role in ecosystem services such as food provision, climate regulation, nutrient cycling, pest and disease control, and habitat support for soil fauna and microbiota (Lehmann et al., 2020; Janzen et al., 2021; Friedrichsen et al., 2021). Expanding further, soil health encompasses contributions to human health, well-being, and societal values, linking directly to the SDGs (Veerman et al., 2020). These broader definitions also integrate stakeholder values, underscoring the need for clear, accessible descriptions and cost-effective methodologies. The soil health concept functions as a 'boundary object', bridging knowledge and management to foster collaboration and actionable outcomes (Wood and Blankinship, 2022). However, soil health should focus on measurable indicators rather than management practices, as the latter aim to improve soil health and evolve with experimental findings, such as those from 'living labs' (Bouma, 2022b; Bouma and Scrope, 2024).

3 Limitations of Current Definition

Efforts to make soil health a holistic concept have resulted in definitions that include diverse elements such as ecosystem services, the ~~Sustainable Development Goals (~~SDGs~~)~~, societal values, management practices, and stakeholder perspectives. This breadth ~~while ambitious,~~ makes soil health difficult to measure~~:~~, as 'Anything that is infinitely defined is, ultimately, undefined and undefinable' (Sojka and Upchurch, 1999). Identifying and quantifying specific indicators to capture this broad scope remains a significant challenge (Baveye, 2021; Wood and Blankinship, 2022), leading to criticisms of the concept's vagueness (Janzen et al., 2021). While some authors embrace this vagueness as an opportunity for new ideas (Janzen et al., 2021) or as a principle in itself (Lehmann et al., 2020), others argue that soil health serves better as a communication tool than a scientific framework (Powlson, 2020).

Harris et al. (2022) challenged the popular notion of soil as a 'living' entity, advocating for a holistic view that considers all soil constituents, interactions, and feedback mechanisms, rather than continually broadening the concept. Although their proposal lacks a concrete implementation strategy, it underscores the importance of grounding the soil health concept in scientific understanding before setting expectations for what healthy soil can achieve. ~~A clearer, more objective definition of soil health, aligned with scientific principles, is essential. As Lord Kelvin aptly noted, 'When you cannot measure it, when you cannot express it in numbers...you have scarcely, in your thoughts, advanced to the stage of science' (Baveye, 2021).~~

Current definitions often prioritise a soil's ability to provide human-desired ecosystem services over its intrinsic properties (Kibblewhite et al., 2008; FAO and ITPS, 2015; Fine et al., 2017; Bonfante et al., 2020; Lehmann et al., 2020). However, equating soil health solely with its capacity to deliver services for humans is inadequate, much like assessing human health purely by economic output or productivity. A more effective approach is to focus on the inherent state of the soil ecosystem and its ecological functions. Ecosystem functions—representing the processes and structures within an ecosystem—provide an objective, value-neutral framework for assessing soil health, distinct from ecosystem services (De Groot et al., 2010; Manning et al., 2018).

Some argue the soil health concept is unnecessary, suggesting that soil scientists can address issues like soil functioning, degradation, and carbon sequestration without it (Baveye, 2021). However, the concept remains valuable. It has advanced scientific understanding of soil biology (Lehman et al., 2015), highlighted its connections to human health (Brevik et al., 2020), and proved an effective tool for science communication. The term 'soil health' resonates with the public, fostering awareness of soil science, agroecology, and conservation (Wander et al., 2019; National Resources Conservation Services of the US Dept. of Agriculture, 2019), and supports citizen science initiatives that enhance soil knowledge (Pino et al., 2022). ~~To fully realise the potential of the soil health concept, its limitations must be addressed. Central to this is improving the ability to measure soil health. Embracing the concept requires robust methods to quantify it effectively (Bouma, 2021).~~To fully realise the potential of the soil health concept, a more precise, objective definition of soil health, aligned with scientific principles, is essential. Central to this is improving the ability to measure soil health quantitatively and robustly. As Lord Kelvin aptly noted, 'When you cannot measure it, when you cannot express it in numbers...you have scarcely, in your thoughts, advanced to the stage of science' (Baveye, 2021).

4 Current Soil Health Assessment Frameworks

Numerous frameworks exist for assessing soil health (Table 1). These typically involve selecting indicators, sampling guidelines, collecting and preparing soil samples, conducting laboratory analyses, interpreting results, setting thresholds, and integrating findings into an index if desired (Rinot et al., 2019). Prominent frameworks include the Soil Management Assessment Framework (SMAF) (Andrews et al., 2004), the Comprehensive Assessment of Soil Health (CASH) (Idowu et al., 2008), and the Soil Quality Index (SQI) (Andrews and Carroll, 2001). Originally developed for soil quality evaluation, these approaches were later adapted to assess soil health as the concept evolved (Table 1).

While the soil health concept is relevant to all terrestrial ecosystems and even aquatic and marine soils (Walden et al., 2024), most assessment frameworks focus on agriculture, aiming to identify productivity constraints and guide land managers toward sustainable practices (Andrews and Carroll, 2001; Andrews et al., 2004; FAO, 2008). Frameworks like SMAF and CASH were developed primarily using data from North American farms (Wade et al., 2022), limiting their applicability to other regions or ecosystems. Recent efforts to expand the scope include frameworks addressing broader soil functions, such as carbon sequestration, biodiversity, and water regulation (Debeljak et al., 2019; Bonfante et al., 2020; Reijneveld et al., 2024). However, these remain largely agronomic, which is fine if that is the intended use, but further research is needed to broaden their applicability to other forms of land use (Wood and Blankinship, 2022).

Soil health assessments in non-agricultural systems, such as natural ecosystems, lag significantly behind, often lacking proper thresholds that so far only apply to agriculture and forestry. Indicators could be the same, but thresholds would be different.

Another limitation is scale. Most frameworks operate at the pedon or field scale, neglecting landscape-level processes such as nutrient runoff, soil redistribution, and climate change impacts (Magdoff et al., 2021; Vereecken et al., 2016). While frameworks like Su et al. (2018) address larger scales, such approaches remain rare.

Despite advancements, there is no universally accepted framework or standardised procedure for soil health assessment, particularly outside agriculture (Deel et al., 2024; Wood and Blankinship, 2022). This lack of consensus hampers the societal acceptance of soil health and its integration into ecological restoration and other disciplines (Gann et al., 2019).

5 Soil Health Indicators

Soil health is a multi-faceted concept that necessitates measurable indicators for assessment. These indicators—encompassing physical, chemical, and biological properties—are closely related to ecosystem services, which have an interdisciplinary character. Bünemann et al. (2018) reviewed soil health assessments and identified over 100 indicators grouped into 50 categories, with 27 frequently used across studies. This diversity complicates the selection of appropriate indicators for ~~effective~~practical soil health evaluations. Table 2 highlights 20 indicators: 10 physical, 12 chemical, and 8 biological.

The selection of indicators is guided by several widely accepted criteria (Bünemann et al., 2018):

1. Relevance to soil functions and ecosystem services.

Table 1. Current soil health assessment frameworks and approaches.

Soil Health/Quality Assessment Frameworks or Approaches	Status	Soil/Land-Use/Region Based On	Scale	Adaptability	Sampling and Measurement Method	Indicator Selection	Interpretation	Integration
Visual Soil Assessment (FAO, 2008)	Established	Agriculture	Field	No	Field test and visual assessment	Expert decision	Ordinal scale look-up table	Weighted addition
Soil Vital Signs (O'Neill, 2005; Amacher et al., 2007)	Established	Forest	Field	No	Sampling design reference	Expert decision	Ordinal scale look-up table	Simple addition
SQI (Andrews and Carroll, 2001)	Established	Agriculture	Field	No	Lab method reference	Principal component analysis	Scoring functions	Simple addition
SMAF (Andrews et al., 2004)	Established	Agriculture	Field	No	Not specified	Expert decision	Scoring functions	Simple addition
CASH (Idowu et al., 2008; Moebius-Clune, 2016; Fine et al., 2017)	Established	Agriculture	Field	No	Sampling instruction and lab method reference	Expert decision	Scoring functions	Simple averaging
Biofunctool (Thoumazeau et al., 2019)	Proposed & Case Study	Agriculture & Forest	Field	No	In-field and laboratory assessment	Expert decision	Scoring functions and lookup tables	Multivariate analysis weighting
Rinot et al. (2019)	Proposed	Not specific	Not specific	Yes	Not specified	Statistical method	Scoring functions	Least square model
Haney Soil Health Test (Haney et al., 2018)	Established	Agriculture	Field	No	Lab method reference	Literature knowledge	Expert decision	Simple multiplication
Solvita Soil Health Tests (Laboratories, 2021)	Established	Agriculture	Field	No	Lab method reference	Not specified	Scored against highest expected value	Simple averaging
Soil Navigator Decision Support System (DSS) (Debeljak et al., 2019)	Established	Agriculture	Field	No	Not specified	Expert decision	Cognitive models	Not specified
Creamer et al. (2022) and BIOSIS (Zwetsloot et al., 2022)	Proposed	Not specific	Field	No	Not specified	Literature review, expert opinion, and logical sieve	Cognitive models	Not specified
Bonfante et al. (2020)	Case study	Agriculture	Field	Yes	Not specified	SWAT model	SWAT model	NA
Su et al. (2018)	Case study	Not specific	Landscape	Yes	Not specified	Literature knowledge	Mechanistic models	NA
Wade et al. (2022)	Proposed & Case Study	Agriculture	Landscape	Yes	Not specified	Factor analysis	Exploratory factor analysis, confirmatory factor analysis, and structural equation model	NA
Maaz et al. (2023)	Proposed & Case Study	Not specific	Landscape	Yes	Laboratory assessment	Principal component analysis	SEM	Latent construct from SEM
SEMWISE (Deel et al., 2024)	Proposed & Case Study	Not specific	National	Yes	Laboratory assessment with specified method	Not specified	SEM	Latent construct from SEM
Soil Health Gap (Maharjan et al., 2020)	Proposed	Agriculture	Field	No	Not specified	Not specified	Compare to 'natural', 'undisturbed' soil	Not specified

Note: The abbreviations used are: CASH - Comprehensive Assessment of Soil Health, SEM - Structural Equation Modelling, SEMWISE - Structural Equation Model for Well-Informed Soil Evaluation, SMAF - Soil Management Assessment Framework, SQI - Soil Quality Index, SWAT - Soil & Water Assessment Tool, NA - not applicable.

2. Sensitivity to spatial and temporal variations from perturbations and management practices.

3. Practicality, affordability, and rapid measurability.

4. Reliability and reproducibility of measurements.

5. Ability to provide actionable management insights.

Despite these criteria, no standardised method exists for selecting scientifically robust and practical indicators across different land uses, ecosystems, and scales. Indicator selection often relies on expert judgement, which introduces subjectivity and limits methodological transparency (Rinot et al., 2019) (Table 1). Subjectivity is further influenced by specific management goals and the investigator's familiarity with the indicators (Wade et al., 2022). Frameworks such as SQI and CASH (Table 1) attempt to mitigate subjectivity by using statistical techniques like principal component analysis (PCA) to identify indicators that explain variability among land-use and management treatments (Chang et al., 2022). However, this may prioritise indicators responsive to management changes while overlooking those offering unique soil health insights (Rinot et al., 2019; Wood and Blankinship, 2022).

Methods that evaluate indicators based on specific criteria (Niemeijer and De Groot, 2008) or site-specific performance (Griffiths et al., 2016; Thoumazeau et al., 2019) are valuable but often neglect interrelationships among indicators (Niemeijer and De Groot, 2008). Improved approaches consider mechanistic interactions between indicators and the soil functions they represent (Creamer et al., 2022). For instance, the Soil Navigator decision support system (DSS) uses a hierarchical multi-criteria model to link soil functions with sub-functions based on literature and expert insights into causal relationships among soil properties, environmental data, land use, and management (Debeljak et al., 2019). Although primarily designed for croplands and grasslands, this DSS informs field-scale applications (Debeljak et al., 2019). Similarly, Creamer et al. (2022) and BIOSIS (Zwetsloot et al., 2022) (Table 1) have developed cognitive models with hierarchical structures to elucidate the relationships between soil biota and soil processes contributing to specific functions. These models employ a logical sieve framework to score indicators, though they currently emphasise biological indicators and require further development to integrate physical and chemical properties (Creamer et al., 2022).

Reijneveld et al. (2024) used a relatively simple procedure to allow application in practice, applying four physical, two chemical and one biological indicator with carbon in a central position. They did not define an 'average' soil health value but focused on individual values, allowing research to focus on indicators that did not meet their threshold. Their work emphasises interdisciplinarity and ecosystem services, aligning with several SDGs, including SDG15 (Life on Land), linking with SDGs 2 and 3 (for producing healthy crops), SDG6 (water quality), SDG13 (climate change mitigation), and SDG15 (preservation of biodiversity).

Climate change is increasingly integrated into soil health assessments, requiring indicators that address its impacts on soil ecosystems and functions. Allen et al. (2011) identified 11 indicators for evaluating climate change effects, primarily biological, but only four are used frequently in soil health assessments.

6 Measuring Soil Health Indicators

Many soil health assessment frameworks provide rudimentary soil sampling guidelines. For example, CASH (Table 1) recommends combining samples from five to ten subsoil locations along a zig-zag transect (Moebius-Clune, 2016). Other frameworks suggest general strategies, such as random sampling, W-shaped walks, or circular transects (Stott, 2019), but these methods often fail to accurately capture soil variability. A more robust sampling strategy tailored to the assessment's specific purpose is essential (Brus and De Gruijter, 1997). Frameworks like the one proposed by Lawrence et al. (2020) offer structured guidance for improving soil sampling ~~approaches~~in soil health assessments.

While some frameworks recommend visual field assessments (FAO, 2008), most rely on laboratory analyses requiring significant sample processing, such as drying, crushing, sieving, and homogenisation. Laboratory methods depend on specific analytical equipment and standardised procedures but are often time-consuming, expensive, and procedurally complex (Viscarra Rossel and Bouma, 2016; Hurisso et al., 2018; Haney et al., 2018). Moreover, these methods may not accurately reflect actual soil conditions. For instance, plant-available nutrients are typically extracted using chemical reagents absent in natural soils (Haney et al., 2018), and sample preparation can disrupt soil structure, impacting assessment accuracy (Inselsbacher et al., 2011). Variations in nutrient availability due to plant strategies and environmental factors further complicate interpretations (Lambers et al., 2008). Additionally, the delay between sampling and analysis can compromise results, particularly for rapidly changing indicators like plant-available nutrients (Chen and Xu, 2008).

Laboratory testing is subject to variability both between and within laboratories (Viscarra Rossel and Bouma, 2016; van Leeuwen et al., 2022). Significant inconsistencies ~~have been observed~~exist for routine indicators and new ones, such as permanganate oxidisable carbon (POXC), analysed by accredited laboratories or using standard methods (Hurisso et al., 2018; Wade et al., 2020). Such variability can amplify marginal errors, leading to deviations in soil health assessments and management recommendations (Viscarra Rossel and Bouma, 2016).

Logistical challenges of laboratory analyses include slow turnaround times, large costs, and environmental impact (Viscarra Rossel et al., 2011). These factors become more pronounced with increasing numbers of indicators and sample sizes (Bünemann et al., 2018; Lawrence et al., 2020). The growing demand for fine-resolution soil data across ~~large~~ spatial and temporal scales highlights the limitations of current laboratory methods.

The assessment of soil health by Reijneveld et al. (2024) could only be realised by applying innovative methods to assess the contents of heavy metals, biocides and microbiological conditions. Without these methods a meaningful assessment would not have been possible.

7 Interpreting Soil Health Indicators

Conventional soil health assessment frameworks often interpret indicators using scoring curves or ordinal-scale look-up tables to generate an index value (Table 1). While ordinal-scale tables provide semi-quantitative assessments, they can introduce between-assessor bias. Scoring curves transform numerical indicators into unit-less continuous values (typically 0 to 1, with 1 indicating healthy) (Wymore, 2018; Karlen and Stott, 1994). These curves are based on assumptions about the relationship between indicators and soil health outcomes, such as ‘more is better’, ‘less is better’, or ‘optimum’ scenarios, which may oversimplify and misrepresent complex soil dynamics (Wood and Blankinship, 2022; Maaz et al., 2023).

An alternative approach involves comparing indicator values to those from undisturbed, natural, or healthy reference sites (Maharjan et al., 2020), but defining and applying reference conditions across diverse land uses remains a challenge (Kennedy et al., 2019; Janzen et al., 2021). Conventional methods help identify differences in management practices (Stewart et al., 2018), but they often fail to establish whether these practices improve soil health or whether the indicators are sensitive enough to differentiate soil conditions (Wood and Blankinship, 2022). ~~This underscores~~These gaps ~~in~~reveal our limited understanding of how indicators connect to overall soil health (Creamer et al., 2022).

To address these limitations, the Soil Navigator DSS (Debeljak et al., 2019) introduced a framework that decomposes complex soil functions into sub-functions based on soil, environmental, and management interactions derived from expert knowledge and literature (Creamer et al., 2022) (Table 1). Initially developed for croplands and grasslands, this approach was later expanded to include biological indicators, with ongoing development for physical and chemical aspects (Creamer et al., 2022). More recent data-driven methods improve interpretation by analysing the covariation between indicators and latent variables describing soil health while accounting for measurement errors (Borsboom et al., 2003; Wade et al., 2022; Deel et al., 2024). These methods simultaneously interpret indicators, focusing on structural relationships rather than predefined assumptions (Maaz et al., 2023).

Some researchers have also integrated soil health interpretation with soil-water-atmosphere-plant ecosystem models (Table 1). For example, the InVEST model assesses freshwater yield as a soil ecosystem service at landscape scales (Su et al., 2018), while the SWAP model evaluates soil health under varying climate change scenarios (Bonfante et al., 2020). These models enable systematic assessments of soil functions at broader scales through simulation (Su et al., 2018). However, understanding the complex mechanisms underlying soil health remains a significant challenge due to the intricate interactions of soil processes and functions (Vereecken et al., 2016; Vogel et al., 2023). Furthermore, large-scale applications of soil-water-atmosphere-plant ecosystem models are challenging due to system complexity, scarce high-resolution field data, poorly constrained parameters from limited measurements, and insufficient empirical observations for calibration (Vereecken et al., 2016; Pongratz et al., 2018).

Threshold and target values for soil health indicators are critical for connecting indicator interpretation with management and policy (Bouma and Reijneveld, 2024). Target values represent achievable management goals, while thresholds identify critical points of soil function decline that necessitate intervention. ~~These thresholds should be informed by scientific research~~Scientific understanding must inform indicator thresholds (Matson et al., 2024; Agency, 2023). Reijneveld et al. (2024) emphasises separating indicators and defining threshold values to distinguish between ‘good’ and ‘not yet good enough’, allowing research to focus on indicators that fall short. ~~Progress towards sustainability can be assessed by the number of thresholds met, with full sustainability achieved when all indicators meet their thresholds.~~

The European Environment Agency has already defined threshold values for key indicators (Agency, 2023). A recent review summarised four methods for establishing threshold or target values: (1) using fixed values based on existing research or practical experience, (2) using values from reference sites, (3) placing indicator values within the distribution of similar soils (stratified by soil type, land use, and climate), and (4) assessing relative changes in indicator values over time (Matson et al., 2024). The relative change method, identified as the most promising, relies on representative chronosequence data, significantly increasing sampling demands (Matson et al., 2024).

Quantitative research is limited, particularly for indicators linked to multiple soil functions, such as soil organic carbon storage, and for those with complex interactions. Rapid and cost-effective methods for assessing soil health indicators are urgently needed to support the development of actionable thresholds and targets tailored to diverse soil types, ecosystems, land uses, and at multiple scales.

8 A Soil Health Index

Many soil health assessment frameworks (Table 1) integrate indicators into a composite soil health index to simplify communication with stakeholders. However, achieving a scientifically robust yet uncomplicated integration method remains challenging. Current approaches—such as addition (Andrews and Carroll, 2001), averaging (Moebius-Clune, 2016), multiplication (Haney et al., 2018), or weighted combinations assume linear, independent contributions of indicators to soil health, failing to account for ecosystem-specific context dependencies (Wood and Blankinship, 2022). In weighted approaches, the challenge lies in determining appropriate weights. Data-driven methods, like principal component analysis for assigning weights (Yu et al., 2018), provide one solution but may bias results toward indicators sensitive to management or disturbance, overlooking those more directly linked to soil functions (Rinot et al., 2019). Emerging frameworks attempt to address these limitations using multi-criteria decision models (Debeljak et al., 2019), cognitive models (Creamer et al., 2022), and structural equation models (Maaz et al., 2023; Deel et al., 2024) (Table 1).

A single soil health index or score is often inadequate for guiding management decisions. Individual indicators, such as soil carbon or structure, provide actionable insights, e.g., adding manure to increase carbon or adjusting tillage to improve structure, while a composite index lacks this specificity (Baveye, 2021; Powlson, 2020). Reijneveld et al. (2024) decided, therefore, not to define a single soil health index. Demonstrating that specific indicators do not meet their threshold allows a focused research effort on such indicators. Regardless of the approach, ensuring that indices remain accessible to stakeholders while retaining scientific validity is therefore critical. Simplified outputs facilitate communication and adoption, but we must maintain the methodological rigour underpinning them to safeguard credibility and prevent misguidance. ~~Possible future approaches for integrating soil health indicators into an index should~~Possible future approaches could adopt a multi-tiered framework, in which individual actionable indicators complement composite indices. For example, the Global Agro-Ecological Zones (GAEZ) integrates data using structured, multi-tiered models that layer agro-climatic, edaphic, and management-specific constraints to generate spatially explicit cropping suitability and yield advice (Fischer et al., 2000). Such approaches would balance simplicity with scientific rigour, summarising complex interactions among indicators while also offering spatially-explicit quantitative information on individual soil properties, processes, and functions to support targeted management actions (Hussain et al., 2022).

9 ~~An Ecological Focus for Soil Health~~An integrative framework for soil health assessments

Soil health assessments often exhibit bias, focusing primarily on ecosystem services tied to human values, agriculture, and societal goals, including the SDGs (Figure 1, Table 1) (Kibblewhite et al., 2008; FAO and ITPS, 2015; Fine et al., 2017; Bonfante et al., 2020; Lehmann et al., 2020). While this focus has ensured policy relevance, it has also reinforced ambiguity and competing definitions, leaving the concept of soil health vague and subjective (Powlson, 2020; Baveye, 2021; Janzen et al., 2021). For instance, in a southern Alberta grassland, Janzen et al. (2021) showed that agronomic criteria deemed the soil 'unhealthy' due to low organic matter content, alkaline pH, and thin topsoil, whereas an aesthetic landscape evaluation rated it as 'healthy'. Both perspectives used similar indicators but applied different criteria based on land-use context. Such divergence illustrates how human-centric framing can obscure ecological value, and why an objective, ecologically grounded framework is needed. Without standardised procedures, soil health remains contested and marginalised in regulation (Baveye, 2021), often replaced by generic management measures assumed, rather than demonstrated, to promote sustainability (Bouma and Scrope, 2024). The scientific community cannot, therefore, afford to delay further development of operational procedures to assess and judge soil health.

We propose ~~reorienting soil health towards a more ecological perspective, emphasising the functioning of soil systems and using robust, innovative methodologies~~an integrative framework that reorients soil health assessment towards ecological foundations while maintaining relevance to human needs. The framework positions soil health within two interrelated but distinct contexts: natural ecosystems and socio-cultural domains Figure 2. By grounding soil health in its intrinsic ecological functions, the framework counters the ecosystem-services bias and shows how societal benefits flow from these foundational processes.

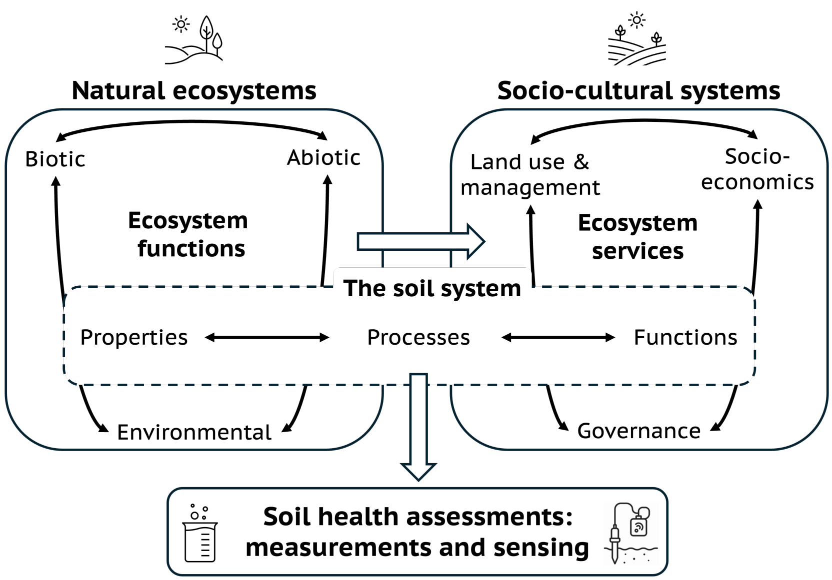

Figure 2. A framework for soil health assessments that places soil within ecosystem and socio-cultural contexts.

In this framing, soil health arises from the interplay of its physical, chemical, and biological processes shaped by biotic and abiotic properties and environmental drivers. These processes sustain essential functions such as nutrient cycling, carbon storage, water regulation, and resilience (Hoffland et al., 2020; Gerke, 2022). For example, soil organic matter interacts with mineral surfaces and microbial communities to regulate mineralisation, aggregation, and microbial growth (Hoffland et al., 2020; Vereecken et al., 2016), thereby linking structure and function. From such dynamics emerge the ecosystem services that underpin both ecological and socio-cultural systems (Figure 2).

Humans occupy a dual role in the framework; they are beneficiaries of soil-derived ecosystem services and active participants in shaping soil health through management practices, land use decisions, and cultural values (Figure 2). Recognising this bidirectional relationship ensures that the socio-cultural considerations are integrated without compromising ecological objectivity. Soil health assessments thus move beyond narrow service-based framing, and instead reflect the soil's intrinsic properties, processes and functions, enhancing evidence-based understanding of soil systems, informing ecosystem services and supporting human interests through targeted, evidence-driven management decisions (Neßhöver et al., 2012; Elmqvist et al., 2012).

Operationalising this framework requires measurement methods capable of capturing the dynamic and heterogeneous nature of soil systems. While different methodological pathways are possible, the practical challenge lies in using and developing tools that can integrate across physical, chemical, and biological domains and scale from field plots to landscapes cost-effectively and practically (Figure 2). Meeting this requirement necessitates sensing and data-driven approaches that enable spatially explicit, temporally dynamic, and system-level assessment of soil health (Viscarra Rossel and Bouma, 2016; Viscarra Rossel et al., 2011; Adamchuk and Viscarra Rossel, 2010).

This ecological, value-neutral framework therefore provides universal applicability across ecosystems and land uses, offering a consistent foundation for both scientific inquiry and policy action. In the following section, we show how the sensor-based methods provide the measurement capabilities required to operationalise this framework in practice.

10 ~~Sensing Soil Health~~A Sensor-enabled framework

Building on the framework outlined above, sensing provides the unique measurement capabilities essential for soil health assessment. Quantitative and objective soil health assessments require indicators that accurately capture soil variability, function across diverse ecosystems, and link to ecosystem processes. Proximal and laboratory-based soil sensing meet these criteria by offering rapid, practical and cost-effective measurements (Viscarra Rossel et al., 2011; Viscarra Rossel and Bouma, 2016; Silvero et al., 2023). Combined with remote sensing, these approaches extend assessments to the landscape and regional scales, embedding soil health within broader environmental contexts (Grunwald et al., 2015).

Sensor data often provide precise, higher-resolution, multi-property representation of soil conditions, providing greater ecological relevance than measurements from conventional laboratory procedures and chemical extractions (Viscarra Rossel and Bouma, 2016; van Leeuwen et al., 2022; Haney et al., 2018). Spectroscopy, for example, captures molecular-level information about soil organic matter, minerals and water, while other sensor systems measure elemental, electrochemical, structural, or biological properties with much less disturbance (Viscarra Rossel and Walter, 2004; Lobsey et al., 2010; Hossain et al., 2024;

Shen et al., 2022; Karlen et al., 2021). Advances in data analysis, machine learning, AI, and chemometrics further enhance interpretation, enabling the extraction of meaningful ecological indicators from complex multi-sensor datasets (Viscarra Rossel et al., 2024; Teng et al., 2018; Deng et al., 2013).

Sensing is well suited to the socio-ecological framework (Figure 2) because it can quantify mechanistic pathways that connect soil to ecosystem processes. Unlike conventional soil analysis that relies on disruptive methods and delayed results, sensors enable in situ and ex situ (near-) real-time measurements. Proximal soil sensors deployed directly in the soil can capture physical, chemical and biological signals under natural conditions, thereby resolving dynamics from rapid fluxes to seasonal cycles and linking measurements directly to ecosystem functions. Sensing in the laboratory, by contrast, can serve a complementary purpose. For example, under controlled conditions, it enables high-throughput, standardised analysis, supports calibration and validation, and allows systematic exploration of soil properties across large sample sets and at different scales (e.g. Viscarra Rossel et al., 2016, 2014). Together, these two modes of sensing, proximal and laboratory, in combination with conventional analysis and remote sensing (Figure 3), offer synergistic pathways for enhanced understanding of soil processes. In situ deployments reveal context-specific variability and emergent dynamics. Laboratory sensing provides thorough testing and, in conjunction with conventional laboratory analyses, yields reproducible reference data for calibration and validation.

Therefore, sensing enables the extraction of meaningful soil indicators from sensor data, positioning sensing as a transformative tool for a next-generation of soil health assessment and monitoring (Buters et al., 2019; Viscarra Rossel and Bouma, 2016; Reijneveld et al., 2024).

10.1 Implementing the sensor-based framework

The assessment framework in Figure 3 connects ecological objectives with sensor-enabled measurements, establishing a standardised yet adaptable pathway for soil health assessment across ecosystems. The implementation begins by defining objectives and identifying the key ecosystem functions(e.g. carbon storage, biodiversity support, nutrient cycling) that balance ecological integrity with societal needs (Figure 2). Indicators are selected using, e.g. multi-criteria methods (e.g. Debeljak et al., 2019) that prioritise ecological relevance, sensitivity to environmental change, and compatibility with cost-effective sensor technologies, while also identifying complementary laboratory analysis, calibration, and validation needs (Figure 3).

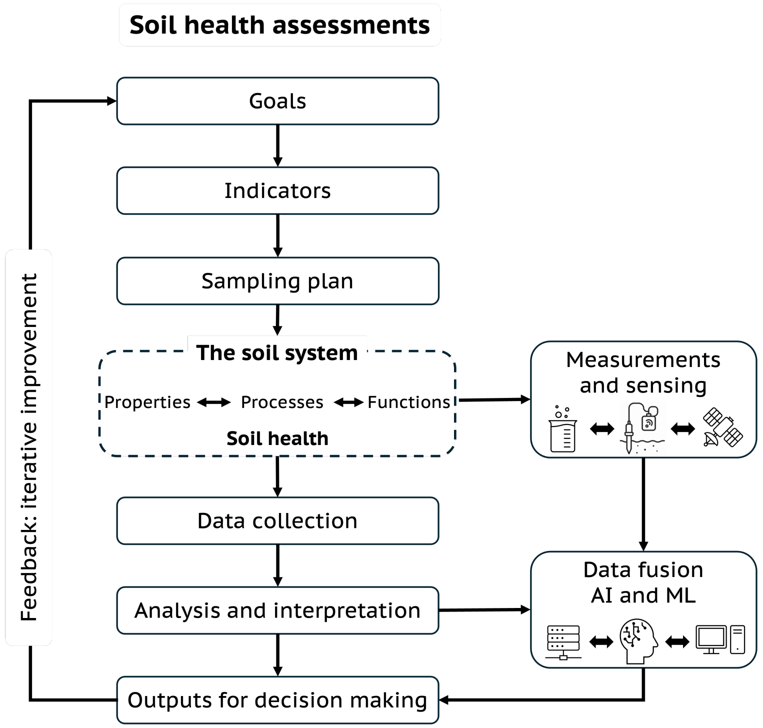

Figure 3. Sensing-enabled soil health assessments.

Then, a sampling strategy is designed to match ecosystem-relevant spatial and temporal scales, making use of the sensors' capacities for making many more measurements and continuous monitoring. Measurements are made through a combined sensor-laboratory approach to provide unique ecological insights and assessments (Figure 2). In this framework, the data collection must also adhere to rigorous, standardised protocols for measurements, calibration and quality assurance, keeping in mind the need for quantifying and propagating uncertainties.

Once collected, the multisensor data is analysed and interpreted using methods such as sensor-data fusion, machine learning, AI or chemometrics (Figure 3), which transform the sensor signals into the indicators, which, for example, might be benchmarked against reference sites, distribution-based thresholds, or temporal trends. The outcomes are then used with decision-support frameworks that deliver actionable guidance for land management while enabling iterative refinement of assessment protocols based on ecological responses and management outcomes.

This approach (Figure 3) highlights why sensing technologies are enabling: unlike conventional laboratory methods, sensing provides more practical and cost-effective measurements (Li et al., 2022), they more adequately capture spatial heterogeneity and temporal dynamics, and they can scale from fields to farms and regions. The strength of sensing is aligned with our proposed framework (Figure 2), emphasising system-level properties, dynamic processes, and spatial-temporal complexity. By operationalising this framework, sensor-based approaches make soil health assessment more rigorous, ecologically grounded, and scalable, bridging the gap between conceptual models of soil function and actionable tools for management and policy.

10.2 Application example–mine site rehabilitation

In this example, implementing the framework (Figures 2, 3) begins with defining the rehabilitation objectives: restoring structural stability for plant establishment, nutrient cycling, chemical amelioration of contaminants, restoring the microbiome and hydrological function for water conservation and erosion control (Young et al., 2022). Indicator selection emphasises restoration-relevant soil properties, including organic carbon, microbial activity, pH, and electrical conductivity, to assess chemical constraints, aggregate stability, available nitrogen and phosphorus for plant establishment, and contamination by heavy metals to determine possible levels of toxicity. A multi-criteria evaluation prioritises indicators sensitive to rehabilitation progress and measurable with sensor technologies (Debeljak et al., 2019). A sampling plan is prepared to address soil and landscape heterogeneity using a stratified design that covers disturbance gradients, such as waste and rock dumps, tailings areas, topsoil stockpiles, and reference undisturbed sites (Young et al., 2022). The design accommodates the higher density of measurement sites that sensing enables, which is not possible with conventional methods. The measurement methods combine proximal and remote sensing with laboratory analysis (Figure 3) to capture the multiple dimensions of soil and landscape rehabilitation. A portable proximal vis–NIR spectrometer provides in situ rapid semi-quantitative assessments of soil clay and iron oxide mineralogy, and organic matter (Viscarra Rossel et al., 2009; Shen et al., 2022), while electrochemical sensors measure field condition pH, EC, nitrate-N, sodium and phosphorus (Viscarra Rossel and Walter, 2004; Lobsey et al., 2010). A portable respirometer is used to measure CO_2 flux as an indicator of biological activity (Bekku et al., 1995; Chimner, 2004; Gyawali et al., 2020). To assess contamination risk, a handheld pXRF sensor detects major elements and heavy metals (Carr et al., 2008). Soil samples are taken for laboratory mid-IR spectroscopy for quantitative estimates of organic and inorganic carbon, clay, sand, and silt content, and cation exchange capacity using local calibrations and validation with reference conventional analysis (Soriano-Disla et al., 2014). Across the rehabilitation site, hyperspectral imaging of vegetation and soil surface properties is complemented by satellites for long-term trajectories (Buma et al., 2024). This integrated approach balances spatial coverage, temporal resolutions, and analytical accuracy in tracking soil health and rehabilitation progress. Data processing integrates multi-sensor data through sensor data fusion and machine learning models calibrated against laboratory analyses, generating integrated rehabilitation indices that combine chemical, physical, and biological recovery indicators. Threshold interpretation applies multiple benchmarks, regulatory compliance values for heavy metals, functional thresholds for plant establishment, and reference ecosystem targets. The analysis identifies areas showing positive health and rehabilitation trajectories versus those requiring intervention. Decision support provides integrated assessments, including risk maps that highlight soil health and intervention areas, compliance reporting that demonstrates regulatory target achievement, and adaptive management recommendations based on rehabilitation progress. The sensor-enabled approach (Figure 3) significantly reduces assessment costs while providing higher spatial resolution than conventional methods, enabling precise tracking of soil health and restoration success.

~~**11Sensor-basedsoilhealthindicators** Sensing is a valuable tool for assessing and monitoring soil health, as it meets the criteria for effective indicator selection (see above). One of its key advantages is the ability to measure or estimate complementary soil properties. This capability enables cost-effective evaluation~~

~~of multiple indicators, providing a more comprehensive understanding of soil processes, functions, and overall health (Figure 2). Unlike conventional methods, sensing systems are particularly adept at capturing spatial and temporal variations, enhancing their effectiveness in soil assessment.~~

~~While sensing may yield less precise measurements per sample than conventional methods, it compensates by allowing for a much higher volume of measurements across diverse locations and times. Such broader datasets can significantly enrich our understanding of soil variability and aid in detecting changes caused by disturbances and management practices (Elliott et al., 2007; Cécillon et al., 2009; Viscarra Rossel et al., 2010). Sensor-based measurements are typically rapid, cost-effective, and require less labour than traditional laboratory techniques. Additionally, the portability of many sensors enables in-field, proximal measurements, eliminating costs associated with sample transport, storage, and preparation (Viscarra Rossel et al., 2011). These attributes make sensing a streamlined and efficient approach for soil health assessment and monitoring (Reijneveld et al., 2024).~~

~~Sensor-based approaches have the potential to revolutionise the evaluation of soil health, especially when integrated with artificial intelligence for data interpretation and remote sensing to capture broader environmental characteristics. This combination of technologies can lead to a deeper understanding and more effective upscaling of soil health assessments, paving the way for next-generation methodologies in soil monitoring.~~

11 Sensing for characterising soil health

Sensing is an enabling tool for assessing and monitoring soil health. Their capabilities, including relevance to soil functions, sensitivity to spatial and temporal variation, rapidity, cost-effectiveness, reliability, and the provision of actionable insights, make sensing effectively meet the criteria for soil health indicator selection (see Section 5). Various sensor technologies are available for measuring soil properties (Kuang et al., 2012; Viscarra Rossel et al., 2011; Silvero et al., 2023; Adamchuk and Viscarra Rossel, 2010). These technologies include laboratory bench-top instruments and portable proximal sensors. Viscarra Rossel et al. (2011) offer a thorough review and classification of soil sensors. Here, we focus on soil sensors relevant to soil health assessments, emphasising those that meet the accepted criteria for indicator selection. Table 2 shows these sensors along with their capabilities to measure commonly used soil health indicators directly or indirectly. 'Direct measurement' refers to measuring a soil health indicator through its direct physical or chemical interaction with the sensor, while 'Indirect measurement' refers to an estimate of a soil health indicator from its relationship with other soil properties that the sensor can directly measure. Although these sensors are currently used in soil science research and some other specific applications (Viscarra Rossel et al., 2011; Silvero et al., 2023), standardised protocols for their use in soil health assessments are underdeveloped.

Diffuse reflectance spectroscopy is the most mature and widely used soil sensing technology (Viscarra Rossel et al., 2022) (Table 2), directly measuring organic and mineral compositions through molecular interactions with visible, near-infrared (vis–NIR), and mid-infrared (MIR) wavelengths (Stenberg et al., 2010; Soriano-Disla et al., 2014). Spectroscopy provides results rapidly, requires moderate to no sample preparation, and can be applied in both laboratory and field settings. Portable, affordable versions are now available (Ji et al., 2016; Shen et al., 2022). The spectra enabling direct or indirect estimation of various chemical, physical, and biological soil health indicators simultaneously (Table 2, sensors 1 and 2) and provide a cost-effective alternative to traditional laboratory analyses (e.g. Li et al., 2022). Portable or hand-held elemental analysers, such as laser-induced breakdown spectroscopy (LIBS) and X-ray fluorescence spectroscopy (XRF), offer rapid, quantitative, and direct, simultaneous measurements of soil elemental composition as well as indirectly measure many soil health indicators that has strong relationship with soil elemental content (Kalnicky and Singhvi, 2001; Bricklemyer et al., 2018; John et al., 2021; Ferreira et al., 2015; Villas-Boas et al., 2016; Senesi et al., 2021; Silva et al., 2020; Jenkins et al., 2024) (Table 2, sensors 3 and 4).

While spectroscopy and elemental sensors measure many properties simultaneously, some critical physical, chemical, and biological properties require more specialised methods. For instance, soil bulk density, essential for assessing compaction and estimating organic carbon stocks, can be measured using active gamma-ray attenuation (AγA) indirectly via the influence of soil density on the amount of gamma radiation is absorbed passing through soil (Lobsey and Viscarra Rossel, 2016; England and Viscarra Rossel, 2018; Pepers et al., 2024) (Table 2, sensor 5). It can also be indirectly estimated using penetrometers (Herrick and Jones, 2002), and electrical ~~conductivity~~resistivity sensor (ER) (Sudduth et al., 2003; Viscarra Rossel et al., 2011)~~, or spectroscopy (Shi et al., 2023)~~. ER and electromagnetic induction (EMI) can directly measure soil apparent electrical conductivity (EC$_a$), as well as sodicity and salinity that directly influence EC$_a$ (Doolittle and Brevik, 2014). Ground-penetrating radar measures soil depth, a critical physical indicator linked to root development, water infiltration, and nutrient availability , by measuring the travel time of electromagnetic waves sent into the ground and reflected back from bedrock (Sucre et al., 2011; Liu et al., 2016) (Table 2, sensor 9). Soil aggregate stability, vital for preventing erosion and supporting root growth, can be assessed with digital imaging techniques such as Moulder (Flynn et al., 2020; M. Fajardo, 2023) or Aggregate STability Assessment using VIdeo Tests (ASTAVIT) (Wengler et al., 2024) (Table 2, sensor 10).

Biological soil health indicators can also be measured by sensing. Portable respirometers with infrared CO_2 analysers measure soil respiration, reflecting microbial activity and organic matter decomposition (Bekku et al., 1995; Chimner, 2004; Gyawali et al., 2020) (Table 2, sensor 11). ~~Soil aggregate stability, vital for preventing erosion and supporting root growth, can be assessed with digital imaging techniques such as Moulder (Flynn et al., 2020; M. Fajardo, 2023) or ASTAVIT (Wengler et al., 2024) (Table 2, sensor 10).~~ Microbial biomass and fungal-to-bacterial ratios can be measured using a smartphone-based microBIOMETER (Nouri et al., 2021). While progress has been made in sensing biological properties, further advancements are needed. Biological soil properties are inherently complex and variable, sensors may not be sensitive or selective enough to detect low concentrations of specific biological markers or differentiate between biologically active and inactive organic matter, as well as interference from soil physical, chemical properties and environmental variables like temperature and moisture Table 3. Studies using vis–NIR spectra combined with machine learning have related soil spectra to ~~microbial biomass, respiration, and bacterial and fungal abundance and~~

Table 2. Sensors for soil health assessment

		Soil sensor technologies											
	Soil health indicators	1 vis–NIR	2 mid-IR	3 LIBS	4 XRF	5 AγA	6 Penetrometer	7 ER	8 EMI	9 GPR	10 Cameras	11 IR CO_2 gas analyser	12 Microfluidics
Physical	Water storage	D	D					I	I	D			
	Bulk density					D				D			
	Particle size (texture)	D	D	I				I	I				
	Structural stability										D		
	Soil depth									D			
	Penetration resistance						D						
	Hydraulic conductivity												
	Porosity					I							
	Aggregation	I	I										
	Infiltration												
Chemical	Organic matter/carbon	D	D										D
	OC fractions (POC, MAOC)	D	D										D
	pH	I	I	I	I								D
	Available P	I	I	I									D
	Available K	I	I										D
	Total nitrogen	I	I	D	D								D
	Electrical conductivity							D	D				D
	Cation Exchange Capacity	I	I										D
	Available N	I	I										D
	Heavy metals	I	I	D	D								D
	Macronutrients (Mg, S, Ca)	I	I	D	D								D
	Sodicity, salinity							D	D				D
	Micronutrients	I	I	D	D								D
Biological	Labile carbon	D	D										D
	Labile nitrogen	D	D										D
	Soil respiration											D	
	Microbial biomass	I									I		D
	Nitrogen mineralisation	D	D										D
	Earthworms	I						I	I				
Suitability of sensing-based indicators for soil health assessment													
Directly measure at least some properties?		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Simultaneously measure wide range of properties?		Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	No	No	Moderately
Quantitative measurement?		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Replicable results?		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rapid measurement?		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Moderately	Yes	Moderately	Yes
Available for portable or in-situ measurement?		Yes	Moderately	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Affordable?		Yes	Moderately	Moderately	Moderately	Yes	Yes	Yes	Moderately	Moderately	Yes	Yes	No
Well-developed and available?		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Key references		Viscarra Rossel et al. (2022); Stenberg et al. (2010); Soriano-Disla et al. (2014); Viscarra Rossel and Hicks (2015); Ji et al. (2016); Shen et al. (2022); Li et al. (2022); Yang et al. (2019, 2022); Huerta et al. (2013)	Viscarra Rossel et al. (2022); Soriano-Disla et al. (2014); Li et al. (2022); Shi et al. (2023); Walden et al. (2025)	Senesi et al. (2009); Bricklemyer et al. (2018); Ferreira et al. (2015); Villas-Boas et al. (2016); Senesi et al. (2021)	Kalnicky and Singhvi (2001); Carr et al. (2008); John et al. (2021); Silva et al. (2020); Jenkins et al. (2024)	Pires et al. (2009); Lobsey and Viscarra Rossel (2016); England and Viscarra Rossel (2018); Reinhardt and Herrmann (2019); Pepers et al. (2024)	Herrick and Jones (2002); Wijewardane et al. (2020); Veum et al. (2017)	Sudduth et al. (2003); Joschko et al. (2010)	Doolittle and Brevik (2014); Lardo et al. (2012)	Sucre et al. (2011); Liu et al. (2016)	Flynn et al. (2020); M. Fajardo (2023); Wengler et al. (2024); Nouri et al. (2021)	Bekku et al. (1995); Chimner (2004); Gyawali et al. (2020)	Pucetaite et al. (2021); Whitesides (2006); Zhu et al. (2022)

Note: Available sensors for soil health assessment and their capabilities. The soil health indicators shown are the most frequently used, as identified by Bünemann et al. (2018). (vis–NIR: Visible and near-infrared spectroscopy; mid-IR: Mid-infrared spectroscopy; LIBS: Laser-induced breakdown spectroscopy; XRF: X-ray fluorescence spectroscopy; AγA: Active gamma-ray attenuation), ER: electrical resistivity sensor; EMI: electromagnetic induction; TOM/TOC: total organic matter or total organic carbon; D: direct measurement; I: indirect measurement based on correlation with directly measurable properties; 'Moderately' indicates partial satisfaction to the criteria.

~~diversity (Hart et al., 2020; Yang et al., 2019, 2022)~~microbial biomass, respiration with excellent accuracy with correlation coefficient above 0.90 (Chodak, 2011), and bacterial and fungal abundance and diversity with up to 73 % of the variability explain by vis–NIR spectra (Yang et al., 2019, 2022). Portable sequencers now facilitate efficient soil organism profiling through eDNA (Kestel et al., 2022; Hellekås, 2021), and nanobiosensors show promise for measuring enzymatic activity (Mandal et al., 2020). ~~However, no sensors are yet available for measuring soil fauna, such as earthworms or arthropods.~~Some studies have found sensing signal could be used as surrogate for earthworm presence and abundance (e.g. Huerta et al., 2013; Joschko et al., 2010; Lardo et al., 2012), but overall, there is still a lack of robust and generalisable measurements of soil fauna using sensors.

Emerging technologies like microfluidics (Whitesides, 2006; Zhu et al., 2022) offer potential for analysing a wide range of soil health indicators (Table 2, sensor 12). These "soil-on-a-chip" systems manipulate fluids in micrometre-scale channels to emulate soil environments, enabling real-time, in-situ monitoring of soil processes (Zhu et al., 2022). Combined with spectroscopy techniques, microfluidics can study interactions between soil microorganisms, the soil matrix, and plant roots, potentially advancing the development of novel, interpretable soil health indicators (Pucetaite et al., 2021). Despite their promise, these technologies are still in early stages of development. Some soil properties remain difficult to measure with sensing, e.g., infiltration and hydraulic conductivity, and research and development are needed.

11.1 Multi-sensor data fusion for soil health assessments

No single sensor can ~~measure~~capture all the attributes that are relevant to soil health ~~indicators~~ (Table 2). Combining data from multiple sensors is a natural strategy to expand the coverage ~~of soil attribute features compared to using individual sensors alone~~needed for soil health assessments. Fusing signals from different sensors (and even remote sensing or lab analyses) expands the range of soil properties measured, yielding more comprehensive datasets than any individual sensor. ~~While overlapping measurements from different sensors may introduce some redundancy, a limited degree of overlap can enhance the robustness of sensor fusion and improve data reliability~~Some overlap in what the sensors measure is inevitable, but a limited degree of redundancy can help improve the robustness and reliability of the fused data. ~~Research~~In practice, integrating complementarity sensors has been shown ~~that integrating data from different sensors improves the predictive accuracy of models for both individual soil health indicators~~to enhance prediction accuracy for soil properties (Wang et al., 2015; Bricklemyer et al., 2018; Omer et al., 2020; Gozukara et al., 2022). Multisensor data fusion provides a broader and often a more precise view of soil condition, ~~benefiting band integrative measures of soil function~~ and overall health (Song et al., 2024; Veum et al., 2017).

However, ~~sensor fusion~~combining data from multiple sensors is not without challenges. ~~Combining datasets can introduce n~~Noise, interference, and inconsistencies can be introduced when fusing heterogeneous data streams (Azcarate et al., 2021). ~~, making careful planning essential.~~ Effective sensor fusion depends on evaluating the independence of sensor information, balancing cost-effectiveness with prediction accuracy, and applying appropriate statistical methods (Azcarate et al., 2021). Furthermore, studies have found that adding data from more sensors may yield diminishing returns in model improvement, underscoring the need for judicious sensor selection (Schmidinger et al., 2024).

11.2 Integrative sensing for soil health assessments

Spectroscopic sensors such as diffuse reflectance spectrometers, LIBS, and XRF (Table 2, sensors 1 to 4) enable the simultaneous measurement of various soil constituents, including molecules, functional groups, and elements, along with their interactions. ~~These measurements generate an integrative 'fingerprint' that can serve as a more comprehensive indicator of soil health~~These measurements generate an integrative 'fingerprint' that reflects a wide range of soil information at once and can itself serve as a composite indicator of soil health (Cohen et al., 2005; Viscarra Rossel et al., 2006; Stenberg et al., 2010; Viscarra Rossel et al., 2022) (Table 3).

This integrative approach offers significant advantages for soil health assessment compared to conventional methods that rely on selecting and measuring an independent and limited set of pre-defined indicators. ~~by mitigating the subjective and inconsistent selection of indicators often associated with traditional methods.~~Instead of selecting individual indicators (e.g. one measure for pH, another for organic carbon, etc), the rich sensor signals inherently ~~Sensor signals provide a comprehensive range of~~contains quantitative soil information on many facets of the soil, thereby minimising bias in the selection of indicators (Maynard and Johnson, 2018) Table 3. As a composite indicator, ~~This makes~~ integrative sensing ~~broadly applicable across diverse soil conditions,~~ provid~~ing~~es ~~an innovative framework for assessing and understanding soil systems~~a more objective and holistic snapshot of soil health, making it more broadly applicable across diverse soils and management conditions. This is particularly valuable in our socio-ecological soil health assessment framework (Figure 2) where we seek the functional status of the soil system.

Integrative sensing can directly predict soil processes, functions, and health by capturing extensive soil information in a single measurement. While promising, this capability requires further research and validation. Spectroscopic methods, particularly vis–NIR and MIR spectroscopy, have proven effective in various applications. For example, researchers have used vis–NIR spectra to predict soil C and N mineralisation (Fystro, 2002; Russell et al., 2002) and litter decomposition (Bouchard et al., 2003). Both vis–NIR and MIR spectra have been used to classify soil health, categorising soils into 'healthy', 'moderately degraded', or 'degraded', as well as to estimate soil health indices in the CASH and SMAF frameworks (Cohen et al., 2006; Elliott et al., 2007; Maynard and Johnson, 2018; Kinoshita et al., 2012; Veum et al., 2015, 2017). Spectra have also been used to classify soil types (Viscarra Rossel and Webster, 2011; Teng et al., 2018) and predict functions such as organic carbon storage, nutrient supply, and biological activity under various conditions, including those affected by wildfire disturbances (Cécillon et al., 2009). In agriculture, spectra have been used to assess soil fertility and evaluate carbon sequestration potential (Vågen et al., 2006; Viscarra Rossel et al., 2010; Deiss et al., 2023; Baldock et al., 2019; Karunaratne et al., 2024). These applications demonstrate the versatility of spectroscopic sensing in providing comprehensive, scalable solutions for assessing soil health and functionality, while addressing challenges in agriculture and environmental management.

11.3 Advantages and limitations of soil sensing for soil health assessments

Sensing provides important advantages for soil health assessment. It enables rapid, non-destructive, and increasingly cost-effective measurements of a wide range of indicators, often delivered in real time and at higher spatial and temporal resolutions than conventional laboratory methods (Viscarra Rossel and Bouma, 2016). These capabilities are especially valuable for supporting data-driven decision-making in situations where traditional approaches may be logistically challenging or economically restrictive. Nevertheless, like any technology, sensing has certain current limitations (Table 3), which can be addressed as the field continues to advance.

Table 3. Advantages, limitations, and possible solutions for sensor-based soil health assessment

Advantages	Limitations	Solutions
• Rapid and (near) real-time	• Initial costs	• Develop more affordable technologies
• Higher spatial, temporal resolution	• Require calibrations	• Create new datasets and methods
• Measures multiple indicators	• Lacking standardised protocols	• Establish standardised protocols
• Less laborious, more cost-effective	• Complex data interpretations	• Develop sensor-data processing software
• Fewer errors and disturbances	• Few biological sensors	• Research biological sensors
• Improved precision (more granular)	• Instrument variability	• Methods to reduce instrument variability
• Enables long-term monitoring	• Require technical upskilling	• Training initiatives (e.g. GLOSOLAN)
• Non-destructive, in-situ analysis	• Limited financial resources	• Partner with universities, NGOs, etc.
• Greater adaptability and scalability		
• Reduced environmental impact		
• Lower indicator selection bias		
• Potential for novel indicators		
• Supports data-driven decisions		
• Supports modelling, mapping and precision agriculture		

Most soil sensors require careful calibration, which can involve two aspects: instrument calibration, where the raw sensor signal is standardised against known references (for example, pH or nutrient sensors calibrated with buffer solutions of known concentrations, or wavelength standards in spectrometers), and analytical calibration, where sensor outputs are related indirectly to soil properties through empirical models. The latter is the case for spectrometers and other sensors that estimate soil health indicators by comparison with conventional analytical methods (Table 2). The reliability of these calibrations depends directly on the quality of the laboratory reference measurements; if the reference values are inaccurate, the sensor estimates will also be flawed (Viscarra Rossel et al., 2022). It is therefore essential that calibration samples are analysed in accredited laboratories that adhere to strict quality control and regular standardisation procedures. Otherwise, the principle of ‘garbage in, garbage out’ applies, where poor-quality reference data inevitably results in poor-quality sensor estimates.

An additional consideration is that while soil sensing measurements may be less precise on a per-sample basis compared to conventional methods, they offer a distinct advantage by enabling far greater sampling densities across varying locations and times. This capacity generates datasets that are not only richer but also more representative of soil conditions and their spatial and temporal variability (Viscarra Rossel et al., 2022). The costs and practical challenges posed by sensor calibrations can be mitigated via the development of global soil sensing data libraries and the use of transfer learning. These approaches can significantly reduce the number of local calibration samples needed, making large-scale sensing applications increasingly feasible and efficient Viscarra Rossel et al. (2024).

Other challenges include variability in performance between different instruments and the performance gap that often exists between field-deployable and benchtop instruments (Table 3). Ongoing research into instrument calibration transfer is addressing these compatibility issues, both across devices Liu et al. (2024) and between field- and laboratory-based instruments (Silva et al., 2025) (Table 3). Biological indicators of soil health also remain a limitation, as they require further advances in both sensing technologies and data analytical methods to capture their complexity more effectively.

In addition to these technical challenges, several practical barriers can limit adoption. All technologies, whether conventional laboratory instruments or newer sensing devices, require considerable upfront investment. However, a key advantage of new sensing technologies is that costs are declining rapidly. For example, portable spectrometers that once cost upwards of US$75,000 can now be acquired in miniaturised versions for less than US$10,000. This growing affordability makes sensing increasingly accessible compared to conventional laboratory analyses, where soil analyses are often tied to centralised infrastructure and large commercial fertiliser companies. As a result, sensing technologies hold promise for transforming soil health management in economically developing countries by enabling a more distributed, bottom-up approach driven by local farmers and communities rather than top-down commercial services (Viscarra Rossel and Bouma, 2016)

The development of standardised protocols for sensor operation, calibration, validation, and reporting is essential to ensure data quality, comparability, and broader uptake. International initiatives such as the Food and Agriculture Organisation of the United Nations (FAO)'s Global Soil Partnership and Global Soil Laboratory Network (GLOSOLAN) are already working towards this goal by harmonising soil analytical methods worldwide, and its dedicated GLOSOLAN-Spec initiative (https://www.fao.org/global-soil-partnership/glosolan-old/soil-analysis/dry-chemistry-spectroscopy/en/) is specifically focused on spectroscopy and soil sensing (Table 3). These initiatives are not only developing guidelines for method standardisation but also building global capacity by training laboratories and practitioners. Such efforts ensure that data from different regions and technologies can be compared and integrated confidently. Building on these developments, pilot projects that test integrated sensing frameworks across diverse ecosystems and land uses could provide valuable opportunities for validation, refinement, and demonstration at scale.

11.4 Recommendations and research needs

Our socio-ecological soil health assessment framework (Figures 2) requires using more advanced technologies and the institutional and procedural conditions to enable its adoption. Within the framework, standardisation is crucial because it underpins every step (Figure 3), from defining the goals, selecting the indicators, to ensuring that the sensor measurements are precise and comparable across ecosystems, laboratories and instruments. Harmonised protocols for sensor operation, calibration, validation and reporting will allow data to be processed and modelled more effectively for decision-making. Such standardisation is needed to make the framework operational and scalable.

Pilot projects provide the link between concept and practice. By trialling integrated sensing frameworks across different ecosystems and land uses, pilots allow validation of methods while adapting them to the socio-ecological contexts and land management practices. Living Labs exemplify this approach by situating sensing within a participatory environment, where farmers, foresters, and other land users co-create knowledge with researchers. Reijneveld et al. (2024) showed that modern sensing of heavy metals, biocides, and microbiological indicators was essential to obtain realistic results in a Living Lab context. Extending this model to non-agricultural Living Labs–forests, rangelands, wetlands, and urban green spaces broadens the framework's reach, embedding soil sensing in the assessment of ecosystem services beyond agriculture. Initiatives such as the EU Mission 'A Soil Deal for Europe', which is establishing a network of 100 Living Labs and Lighthouses by 2030, demonstrate the scalability of this approach and provide a ready pathway to embed our sensing-based framework in decision-making contexts.

At the data level of the framework (Figure 3), global spectral libraries supply the backbone needed to connect sensing with interpretation and outputs. Large, curated datasets (e.g., the USDA NRCS National Soil Survey Centre, Kellogg Soil Survey Laboratory MIR library), and the FAO's GLOSOLAN-Spec initiative are enabling the development of robust, transferable models and ensuring comparability across regions. These libraries align with the socio-ecological framework by reducing the data burden on individual communities and ensuring that local assessments can be connected to global knowledge bases. Recent technical advances in mitigating instrument dissimilarity further improve the portability of models, making it more realistic to deploy sensing across diverse socio-ecological settings.

Equally important, however, is the development of new spectral and soil sensor databases (or libraries) built from soil samples analysed in accredited laboratories under standardised reference methods. Because many sensor calibrations depend directly on the quality of the underlying laboratory measurements, inconsistencies or inaccuracies in reference data will propagate into the models. Imprecise soil analyses in legacy datasets often lead to imprecise sensor predictions, illustrating the well-known dictum of 'garbage in, garbage out.' Establishing sensor-specific libraries underpinned by high-quality, traceable, and standardised laboratory analyses is therefore crucial.

A key barrier to the adoption of our framework is that general (often referred to as 'global') models do not always transfer well to local contexts (Viscarra Rossel et al., 2024). For instance, soil spectroscopic models trained on large, diverse libraries often lose accuracy when applied to local regions, using different instruments or under specific management systems. For communities or agencies with limited resources, collecting sufficient local soil samples to train models from scratch is often not feasible. This 'data gap' might limit the accessibility and scalability of sensing-based soil health assessments. Transfer learning provides a practical solution (Viscarra Rossel et al., 2024). In our framework (Figures 2), TL could link global resources and local implementation. Models of soil health indicators pre-trained on global sensor-specific databases could be fine-tuned with small, targeted local datasets to deliver accurate, cost-effective context-specific predictions. This approach would dramatically reduce the need for extensive new sampling and laboratory analysis, making soil health assessments feasible even in resource-constrained settings, such as in developing countries.

Finally, capacity building will ensure that the framework is adopted and sustained. The limitations identified in Table 3 are best seen as opportunities to strengthen the framework's socio-ecological dimension. Expanded training programs (e.g., through GLOSOLAN), accessible webinars, open standard operating procedures, and cross-sectoral partnerships with universities, NGOs, and agencies to reduce entry costs and disseminate standard operating procedures can democratise access to sensing technologies. Simultaneously, innovations that reduce device costs, improve robustness, and integrate outputs into user-friendly platforms lower barriers for diverse stakeholders. In this way, capacity building becomes part of the social infrastructure of the framework. These efforts, combined with ongoing work to further reduce device costs and improve sensing and modelling capabilities, will enable broader implementation.

12 Conclusions

~~The concept of soil health, emphasising its ecological dimensions, remains broad and challenging to define, often limited by an anthropocentric lens that overlooks its ecological dimensions. Existing soil health assessment frameworks primarily focus on agricultural contexts, failing to adequately address the diverse land-use and ecosystem types that soils support across scales. This narrow approach constrains the potential to fully understand and manage soil's role~~

~~in sustaining ecosystems. We propose adopting a broader ecological perspective that focuses on the soil's ability to function and provide ecosystem services, regardless of land use. This perspective recognises soils as dynamic components of all ecosystems, essential to maintaining ecological balance. However, traditional methods for measuring soil health indicators are often expensive, labour-intensive, and inconsistent in representing field conditions, making them unsuitable for our comprehensive approach. We advocate for using a new generation of sensing-based soil health assessment methods to overcome these limitations. Integrating laboratory, proximal, and remote sensing technologies with AI and machine learning can provide scalable, cost-effective, and precise assessments of soil health and its contribution to ecosystem services. Our review demonstrates that this methodology is now sufficiently advanced to be implemented, offering a transformative tool for ecological soil health assessment. Despite these advancements, the soil science community has yet to develop a universally accepted and operational framework that presents soil health as a compelling concept for policymakers, stakeholders, and the public. Without such a framework, policymakers may base environmental policies on incomplete or flawed scientific foundations. An ecological perspective, underpinned by sensing technologies, provides a unique opportunity to bridge this gap, guiding informed decision-making and fostering a deeper appreciation of the vital role of soils in sustaining ecosystems and human well-being. Time is running out, urgent attention is needed by the scientific community.~~

1. Soil health is broader than agriculture. Current frameworks remain narrowly focused on agricultural contexts, limiting their ability to capture the full ecological dimensions of soil function across diverse ecosystems and land uses.
2. An ecological perspective is needed. Recognising soils as dynamic components of all ecosystems allows us to evaluate their capacity to sustain ecological balance and deliver essential ecosystem services, regardless of land use.
3. Traditional soil health assessment methods that rely on only conventional laboratory analyses are insufficient. Indicator measurements based on conventional field and laboratory approaches are costly, labour-intensive, and often fail to represent real-world conditions. These limitations hinder the development of comprehensive and scalable soil health assessments.
4. Sensing technologies provide a transformative opportunity. Integrating laboratory, proximal, and remote sensing with AI and machine learning now enables cost-effective, scalable, and precise assessments of soil health and its role in ecosystem services.
5. A ‘universal’ framework is still lacking. Despite technological advances, soil science has not yet developed an accepted, operational framework for ecological soil health. Without such a framework, policy and management risk are based on incomplete or fragmented evidence.
6. Our proposed socio-ecological framework offers a way forward. By grounding soil health assessment in an ecological perspective and operationalising it through modern sensing and data-driven technologies, we provide a pathway toward consistent, scalable, and policy-relevant evaluations of soil function. This framework can bridge scientific advances with decision-making, ensuring that soils are recognised and managed as vital to sustaining both ecosystems and human well-being. Time is running out; urgent attention is needed by the scientific community.

Author contributions. YH conducted the literature review and, with RAVR, wrote the manuscript. AC, ZS, and JB provided critical revisions to enhance the manuscript. RAVR conceptualised the review, edited the manuscript and acquired the funding for the project.

Competing interests. At least one of the (co-)authors is a member of the editorial board of SOIL.

Acknowledgements. RAVR thanks the Australian Government's Australia-China Science and Research Fund-Joint Research Centres (ACSRF-JRCs) (grant ACSRIV000077) and the Australian Research Council's Discovery Projects scheme (project DP210100420) for funding. We also thank Dr Johanna Wetterlind for discussion on an earlier draft of the manuscript.

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